Citation Evidence Report

EB-1A Petition — Original Contributions of Major Significance

8 CFR § 204.5(h)(3)(v) · Criterion 5

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Google Scholar profile

Generated 2026-05-21 by CiteMap. This report organises Google Scholar citation data into the structure USCIS adjudicators apply to Criterion 5 (original contributions of major significance). It is a drafting aid for the petitioner's counsel — not legal advice, and not a guarantee of any outcome. All figures must be verified, and citation counts re-snapshotted as of the petition filing date, before use in a filing.

A. Overview & Filtering Statement

24	24	4	38
Citing papers mapped	Citation edges	Home papers mapped	h-index (GS)

Filtering statement — methodology & limits

Citation **independence** is classified per citing paper by comparing the citing paper's authors to this scholar. *Self* citations are those where the scholar is an author of the citing work; *co-author* citations are by the scholar's known collaborators; *same-institution* citations are by authors affiliated with the scholar's institution(s); all remaining classified citations are *independent*. Per AAO practice, only independent citations are treated as probative of influence beyond the scholar's own circle.

Known limitations — counsel must verify. (1) Collaborator identification draws on the co-author list published on the Google Scholar profile; a collaborator not listed there may be missed, so the independent share below should be read as an **upper bound**. (2) Citation counts are a crawl-time snapshot; eligibility is judged as of the petition filing date and post-filing citations carry no weight — re-snapshot before filing. (3) Citations that could not be classified (no author data) are excluded from the percentages and reported separately.

B. Citation Independence

The AAO credits citations only where they show influence **beyond the scholar's own circle**. Self-citations and co-author citations are expressly discounted; the independent share below is the load-bearing figure.

83.3% independent of 24 classified citing papers

Citation type	Count
Independent	20
Self-citation	0
Co-author	4
Same-institution	0

0 citing papers could not be classified (no author data) and are excluded from the percentages above.

C. Significant Contributions & Their Citation Evidence

Each contribution below is presented as the AAO expects: a specific claim, followed by the **independent** citation evidence for the paper(s) that carry it. Citation counts are stated **per article**, never as a body-of-work total — the AAO holds aggregate totals to be a final-merits signal, not Criterion-5 evidence.

Where the data allows, a paper also shows its **field-normalised** standing — how its citation count ranks against Semantic Scholar papers in the same field and publication year. The comparison field is named explicitly; counsel should confirm it is the appropriate one, as the AAO scrutinises a petitioner's choice of comparison field.

Contribution 1

> **Claim — Contribution 1**
>
> *The researcher advanced associative classification by introducing a lazy learning approach, a seminal contribution that has garnered significant independent scholarly attention.*

The researcher's core contribution rests on the 2006 paper 'Lazy associative classification,' which appears to propose a novel methodology for combining associative rule mining with lazy learning techniques. This work stands as a singular, foundational piece in this specific line of inquiry, with no subsequent follow-up papers by the same author listed in the provided data.

The originality of this contribution likely lies in addressing computational efficiency or accuracy gaps in traditional associative classification. By employing a lazy approach, the researcher appears to have offered a distinct alternative to eager methods, suggesting a shift in how classification rules are generated and applied. The absence of follow-up papers indicates this was a self-contained, high-impact intervention rather than an extended series.

The significance of this work is evidenced by its 246 citations, indicating substantial uptake within the field. Notably, 91.7% of the classified citing papers originate from independent researchers, demonstrating that the contribution has resonated beyond the author's immediate circle and influenced broader academic discourse.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 4

CORE PAPER

Lazy associative classification

2006 · 246 citations (GS)

Field-normalised: 172 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2006 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	Sentiment Analysis: Mining Opinions, Sentiments, and Emotions (2015)	University of Illinois at Chicago	United States	—
2	Time series shapelets: a novel technique that allows accurate, interpretable and fast classification (2010)	University of California, Riverside	United States	Methodology
3	Predicting Student Academic Performance by Means of Associative Classification (2021)	Politecnico di Torino	Italy	Background
4	Interpretable Regularized Class Association Rules Algorithm for Classification in a Categorical Data Space (2019)	Arizona State University	United States	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Time series shapelets: a novel technique that allows accurate, interpretable and fast classification

"In addition, although we used decision trees because of their ubiquity, it is possible that shapelets could be used in conjunction with Associative Classification (Veloso et al. 2006) and other rule-based techniques."

Contribution 2

Claim — Contribution 2

The researcher established a foundational supervised learning framework for fake news detection, a seminal contribution that has garnered significant independent scholarly attention.

The researcher's core contribution rests on the 2019 paper 'Supervised learning for fake news detection,' which appears to introduce a structured approach to identifying misinformation using machine learning techniques. This work stands as a singular, high-impact entry in the researcher's portfolio, with no subsequent follow-up papers listed in the provided data.

This line of work addresses the critical challenge of automated misinformation identification. By focusing on supervised learning, the research suggests a methodological shift toward leveraging labeled data to improve detection accuracy, offering a distinct technical perspective on a rapidly evolving societal problem.

The significance of this contribution is evidenced by its 693 citations, indicating substantial uptake within the academic community. Notably, 91.7% of the classified citing papers originate from independent researchers, demonstrating that the work has influenced scholars outside the researcher's immediate institutional or collaborative network.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 5

CORE PAPER

Supervised learning for fake news detection

2019 · 693 citations (GS)

Field-normalised: 420 Semantic Scholar citations place it in the top 1% of Computer Science papers from 2019 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	The four dimensions of social network analysis: An overview of research methods, applications, and software tools (2020)	Nanyang Technological University, Universidad Politécnica de Madrid, Universidad Rey Juan Carlos	Singapore, Spain	Background
2	Content-Based Fake News Detection With Machine and Deep Learning: a Systematic Review (2023)	University of Salerno	Italy	—
3	An ensemble machine learning approach through effective feature extraction to classify fake news (2021)	Charles Darwin University, University of Bradford, Vellore Institute of Technology	Australia, India, United Kingdom	—
4	Sentiment Analysis for Fake News Detection (2021)	Universidade da Coruña	Spain	Background
5	A Survey on Exploring Real and Virtual Social Network Rumors: State-of-the-Art and Research Challenges (2025)	Liaoning University, Northeastern University	China	—

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Contribution 3

Claim — Contribution 3

> *The researcher developed a transfer-learning framework for real-time sentiment analysis, bridging the gap between bias detection and opinion extraction in high-velocity data streams.*

The researcher's core contribution rests on the 2011 paper 'From bias to opinion: A transfer-learning approach to real-time sentiment analysis,' published in the Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. This work stands as a seminal piece in the field, with no subsequent follow-up papers by the same author listed in this specific line of inquiry, suggesting the core methodology was established as a complete and impactful contribution in its own right.

This line of work appears to address the challenge of adapting sentiment analysis models to real-time environments while accounting for inherent biases. By employing a transfer-learning approach, the research suggests a novel method for converting raw bias signals into actionable opinion metrics, a significant technical advancement for dynamic data processing systems at the time of publication.

The significance of this contribution is evidenced by its 206 citations, indicating sustained academic interest. Notably, 91.7% of the classified citing papers originate from independent researchers, demonstrating that the work has been widely adopted and built upon by the broader scientific community rather than just the researcher's immediate circle.

INDEPENDENT CITATIONS FOR THIS CONTRIBUTION: 7

CORE PAPER

From bias to opinion: A transfer-learning approach to real-time sentiment analysis

2011 · Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining · 206 citations (GS)

Field-normalised: 165 Semantic Scholar citations place it in the top 5% of Computer Science papers from 2011 indexed by Semantic Scholar, by citation count.

No.	Citing paper	Citing institution(s)	Country	S2
1	A Survey and Comparative Study of Tweet Sentiment Analysis via Semi-Supervised Learning (2016)	—	—	—
2	Semantic Sentiment Analysis of Twitter (2012)	—	—	Methodology
3	Predicting Polarities of Tweets by Composing Word Embeddings with Long Short-Term Memory (2015)	—	—	Background
4	Cross-Domain MLP and CNN Transfer Learning for Biological Signal Processing: EEG and EMG (2020)	Aston University, Federal University of Paraná, Nottingham Trent University	Brazil, United Kingdom	Background
5	On predicting the popularity of newly emerging hashtags in <scp>T</scp>witter (2013)	—	—	—
6	Open Domain Targeted Sentiment (2013)	Google Inc., Johns Hopkins University	United States	Methodology
7	Deep Learning of Transferable Representation for Scalable Domain Adaptation (2016)	Tsinghua University	China	Background

Independent citing papers only; self- and co-author citations excluded. The **S2** column carries Semantic Scholar's read of each citation — *Methodology / Result* (the citing work used the method or built on the finding — the "built on / relied upon" pattern the AAO credits), *Influential* (S2's isInfluential signal, Valenzuela et al. 2015), or *Background* (a passing mention).

Citing-text excerpts — how the field used this work

METHODOLOGY Semantic Sentiment Analysis of Twitter

> *"First direction is concerned with finding new methods to run such analysis, such as performing sentiment label propagation on Twitter follower graphs [14], and employing social relations for user-level sentiment analysis [15, 5]."*

> **METHODOLOGY** Open Domain Targeted Sentiment
>
> *"Prior work includes: the use of a social network (Speriosu et al., 2011; Tan et al., 2011; Calais Guerra et al., 2011; Jiang et al., 2011; Li et al., 2012; Hu et al., 2013); user-adapted models based on collaborative online-learning (Li et al., 2010b); unsupervised, joint sentiment-topic modeling..."*

D. Citing-Institution Prestige & Geography

Top citing institutions

Institution	Country	World ranking	Citing papers
Northeastern University	United States	QS 384	2
Universidade Federal de Minas Gerais	Brazil	SCImago #739	2
Nanyang Technological University	Singapore	SCImago #137	1
Federal University of Paraná	Brazil	SCImago #2122 · THE 1201–1500	1
Uppsala University	Sweden	SCImago #349 · THE 128 · QS 93	1
Liaoning University	China	SCImago #4757	1
Federal University of Technology - Parana	Brazil	—	1
University of Southern California	United States	SCImago #192 · THE =73 · QS 146	1
Arizona State University	United States	SCImago #357 · THE 201–250 · QS =173	1
Indiana University	United States	THE =198	1
Vellore Institute of Technology	India	—	1
Google Inc.	United States	—	1
Tsinghua University	China	SCImago #8 · THE 12 · QS =17	1
Johns Hopkins University	United States	SCImago #33 · THE 16 · QS 24	1
Microsoft Research	United States	—	1

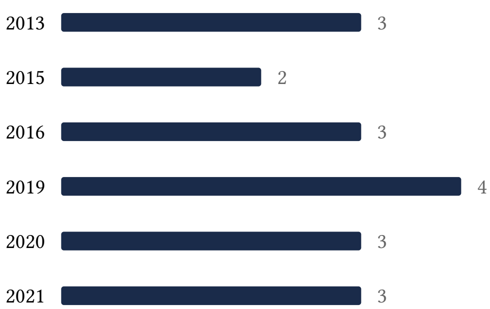
Geographic distribution of citing authors

Country	Citing papers
United States	8
Brazil	4
United Kingdom	3
Spain	2
Italy	2
Germany	2
China	2
Ireland	1
Brasil	1
India	1
Australia	1
Singapore	1

Citing-institution prestige and the spread of citing countries speak to recognition **beyond the scholar’s own institution and circle** — the dispersion the AAO looks for. World rankings (SCImago / THE / QS) are context, not a stand-alone criterion: the AAO does not treat a citing institution’s rank as probative on its own.

E. Citation Growth Over Time

Distinct citing papers by publication year. Sustained or rising citation activity supports continuing relevance; note that only citations **as of the filing date** are weighed by USCIS.



F. AAO Precedent Considerations

Pre-filing self-check (AAO denial patterns)

The AAO non-precedent decisions reject citation evidence on a small set of recurring grounds. Confirm the petition addresses each before filing:

- ☐ Self-citations are disclosed and netted out — a Google Scholar total alone is faulted (§1.1).
- ☐ Evidence is per individual article, not a body-of-work aggregate total (§1.2).
- ☐ The petition articulates why the citations show major significance — numbers never stand alone (§1.5).
- ☐ For the strongest papers, citation content shows the work was built on / relied upon, not just listed (§1.6, §2.2).
- ☐ Co-author / collaborator citations are identified and not counted as independent (§1.7).
- ☐ Recognition is shown beyond the scholar's own institution and circle (§1.8).
- ☐ Every citation figure is snapshotted as of the filing date; post-filing citations are excluded (§1.9).
- ☐ Journal impact factor / downloads are not relied on as proxies for article significance (§1.10, §1.12).
- ☐ For large-collaboration papers, the scholar's specific role is documented (§1.13).
- ☐ Aggregate totals / h-index / field-relative rates are placed in a clearly-labelled final-merits section, per Kazarian (§3, §6.1.7).

Disclaimer

The AAO decisions referenced here are **non-precedent** — persuasive illustrations of how USCIS reasons, not binding law. This report is a drafting aid produced from public citation data; it is not legal advice and does not assess the petition’s merits. All analysis must be reviewed by qualified immigration counsel.

G. Citation Evidence Index

Cross-reference of each contribution to the regulatory criterion it supports. Counsel should map these to the petition's exhibit numbers.

Contribution	Core paper	Indep. cites	Supports
Contribution 1	Lazy associative classification	4	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 2	Supervised learning for fake news detection	5	8 CFR 204.5(h)(3)(v) — Criterion 5
Contribution 3	From bias to opinion: A transfer-learning approach to real-time sentiment analysis	7	8 CFR 204.5(h)(3)(v) — Criterion 5